Trends in Cognitive Sciences

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Review

Interface, interaction, and intelligence in generalized brain–computer interfaces

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A brain–computer interface (BCI) establishes a direct communication channel between a brain and an external device. With recent advances in neurotechnology and artificial intelligence (AI), the brain signals in BCI communication have been advanced from sensation and perception to higher-level cognition activities. While the field of BCI has grown rapidly in the past decades, the core technologies and innovative ideas behind seemingly unrelated BCI systems have never been summarized from an evolutionary point of view. Here, we review various BCI paradigms and present an evolutionary model of generalized BCI technology which comprises three stages: interface, interaction, and intelligence (I3). We also highlight challenges, opportunities, and future perspectives in the development of new BCI technology.

Highlights

Classical brain–computer interface (BCI) systems are moving beyond lab demonstrations to real world applications with the development of associated hardware and software.

Brain–computer interaction systems open up a wide range of BCI applications, especially in neural rehabilitation and human cognitive augmentation.

Brain–computer intelligence systems reveal promising technologies for a new generation of artificial intelligence (AI) as well as a new generation of BCIs.

BCI: from sensation and perception to cognition

A BCI is a direct communication channel between the central nervous system (CNS) and a computer without assistance from the peripheral nervous system [1]. In this sense, any system with direct interaction between a brain and an external device could be considered a BCI system [hereinafter referred to as **generalized BCI** (see Glossary)]. Whereas early BCI technologies provided tools for the motion disabled to communicate with their environments, BCI use has been extended to numerous medical and non-medical applications, including brain state monitoring, neuro-rehabilitation, and human cognitive augmentation. With rapid advances in neurotechnology and AI, the brain signals used for communication between brain and computer have advanced from sensation [e.g., **evoked potentials (EP)**] and perception [e.g., **event-related potentials (ERP)**] levels to higher-level cognition (e.g., goal-directed intentions), bringing BCIs into a new era of hybrid intelligence.

Although many articles have reviewed the history, current status, and future challenges of BCIs [2–9], most focus on specific methodologies, paradigms, or applications. The common principles and core technologies behind seemingly unrelated BCI paradigms have never been summarized from an evolutionary point of view. Here, we describe how BCI technology has evolved since its birth and present an evolutionary model for generalized BCIs, which comprises three progressive stages: I3. We refer to this as the I3 model. In the following sections, we describe the intrinsic nature of evolving technologies according to the I3 model, review various BCI paradigms across the three stages, and discuss the challenges and opportunities in the future development of the BCI technology.

An evolutionary model for generalized BCI technology: I3

The development and evolution of BCI technology can be divided into three progressive stages. In the first stage, interface between brain and computer provides a direct communication channel for disabled patients. In the second stage, more advanced **closed-loop BCI systems** are developed. The interaction between brain and computer in closed-loop BCIs promotes the restoration of human functions in addition to effective device control [4]. In the third stage,

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which is enabled by rapidly developing AI technology, more general platforms for integrating biological intelligence and AI are proposed and developed [10]. To summarize generalized BCI technology from an evolutionary point of view and identify future trends in BCI development, we present a model of I3 (Figure 1). Later, we introduce the components of the I3 model by

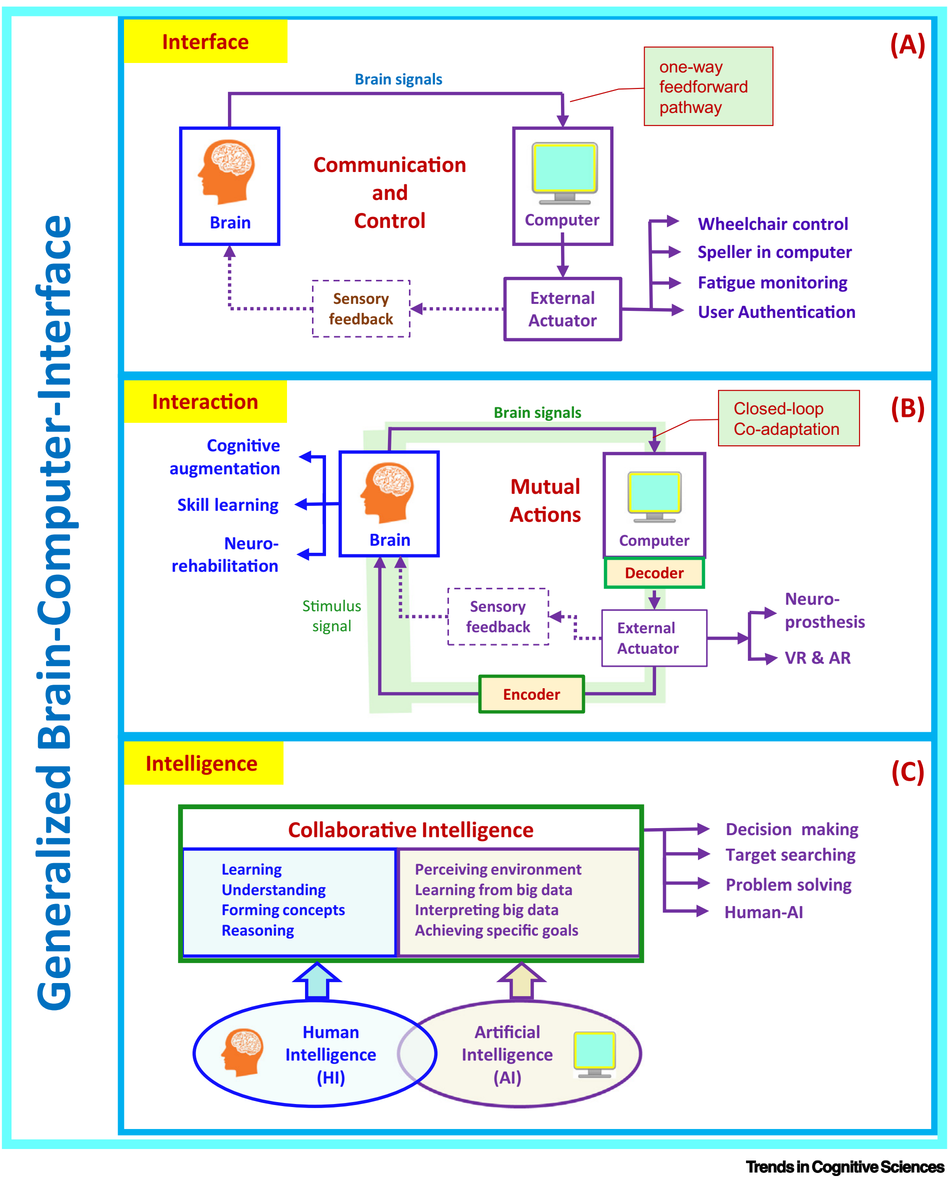

Figure 1. An evolutionary model for generalized BCI technology. (A) Brain–computer interface (BCI): This classical BCI could be thought as a one-way feedforward pathway. Communication and control are its major applications. (B) Brain–computer interaction: the interaction is based on a closed-loop feedback control system with brain-in-the-loop. The system integrates both decoding and encoding components in a loop forming a bidirectional BCI system. Through the mutual actions, the system will change the brain function as well as the status of devices. (C) Brain–computer intelligence: the system converges human intelligence (HI) and artificial intelligence (AI) components in a unified platform. The collaborative intelligence takes full advantage of the complementary nature of HI and AI systems. The performance of a resultant hybrid intelligence system will be superior to a single-modal HI or AI system. Abbreviations: AR, augmented reality; VR, virtual reality.

Glossary

Augmented BCI: extend BCI applications from the current laboratory or clinical environment to real daily life by enabling them to function when individuals interact with the environment.
Closed-loop BCI systems: real-time BCI systems in which the brain and external devices bidirectionally interact with each other.
Cognitive BCI: directly decodes higher-order, goal-oriented cognitive signals to send intuitive BCI commands without goal-irrelevant and indirect thinking.
Electrocorticography (ECoG): uses flexible, closely spaced subdural grid or strip electrodes that are placed directly on surgically exposed brain surface to measure cortical electrical activity. This technique is characterized by high spatio-temporal resolution, broader bandwidth, and excellent signal-to-noise ratios (SNRs).
Electroencephalography (EEG): utilizes electrodes that are placed on the scalp surface to non-invasively measure electrical potentials that arise from activity in the brain. EEG primarily reflects the sum of post-synaptic potentials from cortical neurons.
Event-related potential (ERP): an electrophysiological brain signal that is time-locked to the occurrence of an event. Typically, the latency and amplitude of ERP can be obtained by averaging multiple trials in the time domain.
Evoked potential (EP): an electrical potential that is caused by the nervous system in response to a sensory stimulus. Various stimuli may generate evoked potentials, but visual, auditory, and somatosensory are the most frequently used stimulus types.
Functional magnetic resonance imaging (fMRI): utilizes magnetic resonance imaging to noninvasively measure changes in the blood oxygenation level dependent (BOLD) signal as indication for local brain activity.
Functional near-infrared spectroscopy (fNIRS): calculates the concentration changes of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) in a brain tissue based on the changes of the exiting-photon intensity and the incident-photon intensity, and then characterizes the local neural activity.
Generalized BCI: any system that has direct interaction between the brain and external devices.

describing the core technologies and major applications of generalized BCIs across the three stages.

Classical brain–computer interface

The early BCI systems used for communication and control are called classical BCIs (Figure 1A). For example, BCI spellers have been developed to help patients with motor disabilities communicate with other people [1]. In BCI-based communication and control, most systems will feed back the results (e.g., spelled characters or cursor movements) on a computer screen (see 'Sensory feedback' in Figure 1A) so that users obtain the consequences of their controls in real time. However, if users consciously use feedback information to change their neural or behavioral activities (e.g., BCI-based neurorehabilitation training), the system will form a closed-loop BCI. We discuss these in the next section. The core technologies used in classic BCI systems enable the generation, acquisition, and decoding of brain signals.

In classic BCIs, the methods used to generate brain signals can be either active or passive [7]. To actively generate brain signals, a user can either consciously control mental activities such as motor imagery [11] or intentionally react to stimuli from the external world (e.g., visual, auditory, somatosensory, or oddball stimuli) [12]. For example, BCI paradigms based on actively generated brain signals can allow a user to spell a word, move a cursor, and control a wheelchair or a robotic arm [1,9]. In contrast, the passive generation of brain signals does not require the user to actively participate. **Passive BCI**s have been used to monitor users' cognitive state including drowsiness, intentions, situational interpretations, and emotional states [13–17].

Different techniques, which have different temporal and spatial resolutions, can be used for the acquisition of brain signals related to electrophysiology or metabolism information. Signals related to electrophysiology include **electroencephalography (EEG)**, **magnetoencephalography (MEG)** [18], **electrocorticography (ECoG)** [19,20], local field potentials (LFP), and spike signals collected by implanted microelectrodes. The advantage of these signals is high temporal resolution. Metabolic signals can be collected by **functional near-infrared spectroscopy (fNIRS)** [21], **functional magnetic resonance imaging (fMRI)** [22], and positron emission tomography (PET). Among them, fMRI can provide good spatial resolution and is more sensitive to subcortical brain regions than electrophysiological signals [5], and therefore plays an important role in cognitive research [23]. Importantly, electrophysiological and metabolic signals represent distinct but coupled aspects of neuronal activity.

By analyzing brain signals, the computer can decode the user's intention. A decoder usually consists of three procedures: signal preprocessing, feature extraction, and pattern classification. The main purpose of signal preprocessing is to remove the noise in the recorded signals to highlight the useful components. Feature extraction involves finding the feature components most related to the subject's intention. Pattern classification involves distinguishing the different intentions of users according to the extracted features. Among these procedures, pattern classification is the core algorithm in brain signal decoding [24]. In recent years, AI and machine learning methods have been widely used in brain signal decoding [2,25].

Brain–computer interaction

Unlike classical BCIs, a brain–computer interaction system is a closed-loop feedback control system with a brain-in-the-loop (Figure 1B) [26]. This is also called a bidirectional BCI [27]. Taking the control of a neuroprosthesis as an example, a brain–computer interaction system not only translates neural activities from the primary motor cortex (M1) to control commands, but also transfers the external sensory information from the neuroprosthesis back as somatosensory

Hybrid BCI: combines a BCI with another system(s) that utilize other physiological or technical signals. The purpose is to integrate diverse input signals to achieve better BCI performance.

Magnetoencephalography (MEG): a noninvasive imaging technique that utilizes a superconducting quantum interference device (SQUID) to measure extremely weak magnetic fields outside the head. MEG can directly reflect the magnetic field changes caused by cortical neural activity on a millisecond timescale.

Passive BCI: an interface that derives its output from naturally occurring brain activity during task execution to act as a complementary input providing information about ongoing user mental states (e.g., workload, emotional state, or attention levels).

P300 event-related potential (ERP)-based BCI: a BCI system based on P300 event-related potential that is a positive deflection at approximately 300 ms after a rare and relevant stimulus. P300 signals can be increased in amplitude when the particular stimulus is given greater attention.

Sensorimotor rhythms (SMRs)-based BCI: a BCI system based on mu (8–12 Hz) and beta (18–26 Hz) oscillations in EEG signals recorded over sensorimotor cortex. The amplitudes of SMRs can be modulated using mental strategy of motor imagery.

Slow cortical potential (SCP)-based BCI: a BCI system based on very slow variation of the cortical activity. Positive SCPs correlate with mental inhibition and relaxation, whereas negative SCPs coincide with mental preparation.

Steady-state visual evoked potentials (SSVEPs)-based BCI: a BCI system based on periodic brain responses induced by repeated visual stimulation. SSVEPs appear as an increase in brain activity at the stimulation frequency and its harmonics.

feedback to the primary somatosensory cortex (S1) by electrical stimulation. By receiving motor outputs and sending sensory inputs, a closed-loop neuroprosthesis bidirectionally interacts with the brain. Consequently, as shown in Figure 1B, there are two outputs in the brain–computer interaction system. One path is the controlled external actuator (in purple), and the other is the modulated brain state (in blue). The purpose of the former is similar to that of a classical BCI system. The purpose of the latter is to change the state of the brain to augment human performance. For example, direct modulations of brain activities have been used to treat neurological diseases or improve the capability of healthy people. The core technologies in brain–computer interaction systems include neuromodulation, closed-loop construction, and co-adaption.

The modulation of neural activities is primarily performed in two ways [28]. The first involves applying some physical energy directly to the brain, which is called brain stimulation. Transcranial magnetic stimulus (TMS) [29], transcranial electrical stimulus (TES) [30], transcranial focused ultrasound (tFUS) [31,32], deep brain stimulus (DBS) [33], and cortical stimulus [34] all belong to this category. The second involves neurofeedback training without direct brain stimulation. With instantaneous feedback of neural activities provided by neurofeedback, users can learn to self-regulate brain activities through operant conditioning or volitional control [35]. Different from the communication and control purpose of the classic BCI, neurofeedback has been used as generalized treatment of mental disorders.

The key in implementing interaction is closed-loop construction, in which a major difficulty is how to send the feedback information directly to the brain [36–38]. For example, an upper-limb neuroprosthesis needs to integrate both the motor and sensory modalities to fully restore arm and hand functions during grasping or manipulation of objects. Current electrical stimulation methods such as cortical surface stimulus and intracortical microstimulation can provide sensory feedback to close the sensory-motor loop. However, there are still some limitations of these methods. When applying electrical stimulation, additional problems such as the lifetime of implanted electrodes, artifacts produced by electrical stimulation, and electrochemical safety of electrode–tissue interface arise and remain to be solved [27].

A robust implementation of a closed-loop BCI system depends on the co-adaptation between the brain and the decoder [39–41]. On the one hand, the brain should adapt to the changes in the external environment, and constantly optimize the execution of tasks; on the other hand, the decoder and the external actuators should also learn to adapt to the changes in neural activities and correctly identify the user's intention. Core methods, including auto-calibrated classifier, automatic detection of non-control state, and optimization of speed-accuracy trade-off have been developed to improve BCI performance through co-adaptation. The continuous co-adaptation process is indispensable for a BCI system to maintain good operation [42].

Brain–computer intelligence

With the rapid development of AI in recent years, increasing integration between brain and computer has made it possible to augment human intelligence (HI) using BCI technology. A generalized BCI platform includes components of both HI and AI (Figure 1C). The performance of a resultant hybrid intelligence system will be superior to a single-modal HI or AI system. The increasingly close relationship between HI and AI has allowed BCI applications to expand. In medical applications, BCIs play a role in the rehabilitation treatment of cognitive impairment [43]. In non-medical applications, the collaboration of HI and AI can improve human perceptive abilities or information processing and decision-making abilities [44–47]. The core technologies in brain–computer intelligence systems include cognitive signal generation, coupling human cognitive information to AI computing, and human-AI co-adaptive learning.

The study of brain–computer intelligence systems focuses on higher-order cognitive brain signals, which come from brain regions related to cognitive activities. These signals may arise from diverse areas ranging from rather specific parietal and frontal areas to complex prefrontal networks. The usage of these signals, which usually encode goal-directed intentions, may enable us to accomplish complex tasks intuitively and efficiently [48]. Cognitive brain signals already applied in BCIs include signals related to anticipation and movement preparation, error-related potentials, and correlates of goal-directed movements [43,49].

To realize the collaborative intelligence of HI and AI, it is necessary to extract human cognitive information and couple it into the AI computing system, so as to improve the performance of AI computing. In such a hybrid intelligence system, the capabilities of HI and AI complement each other. Human cognitive ability and the capabilities of computers in fast operations and large storage can be integrated to accomplish the same task collaboratively. For example, the cortically coupled computing (3C) system, which integrates an ERP-based BCI with computer vision, couples cognitive EEG signals into AI computing to improve the speed and accuracy of target image detection [44,46].

Co-adaptation between brain and computer is a fundamental issue in generalized BCIs. In a brain–computer intelligence system, HI and AI are combined together and adapt their behavior based on the information they have received from each other. The study of co-adaptive learning between the two learning systems (i.e., human and AI) has become a major issue from both theoretical and practical points of view [50,51]. Human-AI co-adaptive learning requires humans and machines to collaborate in an adaptive, dynamic, and personalized fashion. The goal is to enable human and AI to learn and work together adaptively and effectively [39,42,52].

History of BCI: an evolutionary point of view

According to the three stages in the proposed I3 model, here we review various system paradigms of BCIs. Figure 2 shows the history of the development of BCI over the past 50 years. Since Vidal proposed and developed the first BCI based on visual evoked potential (VEP) in 1970s [53], several prototype BCI systems came out one after another by adopting different types of EEG signals. The well-known early systems include the **slow cortical potentials (SCPs)-based BCI** [54,55], the **P300 event-related potential (ERP)-based BCI** [56], the **sensorimotor rhythms (SMRs)-based BCI** [57], and the **steady-state VEPs (SSVEPs)-**

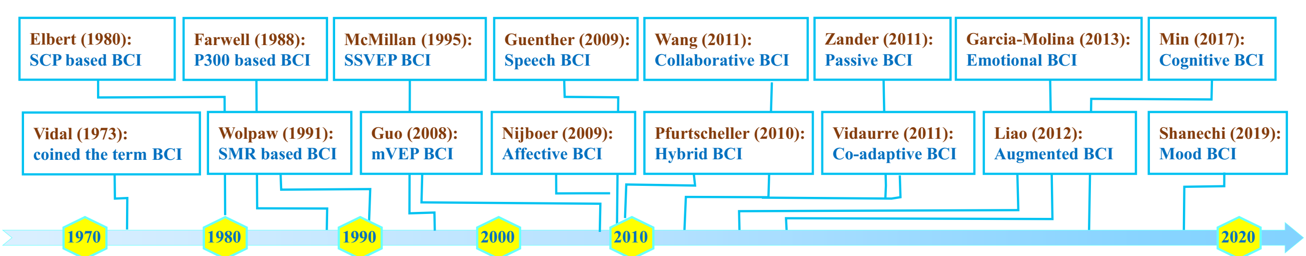

Figure 2. BCI paradigms illustrated in chronological order. The term 'brain–computer interface (BCI)' was first proposed by Vidal in 1970s as an ultimate goal in man-machine communication [53]. In the early years before 2000s, the study of BCI paradigms focused on applying different types of electroencephalogram (EEG) signals, which included slow cortical potentials (SCP) [54], P300 event-related potentials (ERPs) [56], sensorimotor rhythms (SMRs) [57], and steady-state visual evoked potentials (SSVEPs) [58], to realize brain–computer communication. In the past two decades, BCI paradigms have been extended in two major directions. In terms of system implementation, new system paradigms such as hybrid BCI [62], collaborative BCI [63], and co-adaptive BCI [64] have emerged. In terms of applications, new paradigms including speech BCI [79], affective BCI [71], passive BCI [17], augmented BCI [69], emotional BCI [74], cognitive BCI [43], and mood BCI [75] have been proposed and developed. Abbreviation: mVEP, motion-onset VEP.

based BCI [58,59]. These paradigms, which have been referred to as classical BCIs or traditional BCIs, demonstrate the possibility of direct communication between brain and machine.

In the following years, in order to improve the overall performance of classical BCIs, many new paradigms have emerged [3]. The motion-onset VEP (mVEP)-based BCI was introduced to enhance user experience of VEP-based BCIs by avoiding the discomfort caused by the flickering stimulus [60,61]. **Hybrid BCIs** were introduced to achieve higher communication capability by integrating multiple BCI paradigms (e.g., P300 and SSVEP) or fusing other physiological signals such as electromyogram (EMG) into classical BCIs [62]. In another approach, a collaborative BCI that fused ERPs from a group of subjects for collective decision making was demonstrated [63]. After long-term research on relatively independent user training and algorithm development, researchers have obtained the consensus that BCI system runs on the base of real-time interaction between two adaptive controllers (i.e., the brain and the computer [1]). The co-adaptive BCI paradigm that emphasizes mutual learning from both controllers has been introduced to improve BCI performance progressively during long-term operations [64,65]. Such closed-loop systems have also been widely used in the study of neurobiological mechanisms of brain functions such as perception, attention, and memory [66–68]. In recent years, a unified brain–computer intelligence platform has been introduced to integrate HI and AI. New paradigms such as **cognitive BCI**s [43] and **augmented BCI**s [69,70] have been developed to study the cognitive state of people, and even to achieve collaborative intelligence to improve human performance. Other paradigms such as affective BCIs [71–73], emotional BCIs [74], and mood BCIs [75,76] recognize and regulate emotion by understanding the effects of emotional states on brain activities. Here, we have seen BCIs evolve from interface to interaction, and then to intelligence. In the following text, we further explore how two major applications of BCIs have evolved.

BCIs for communication and control mainly address issues related to the generation and translation of brain signals in the interface stage. Thus, major visual, auditory, and sensorimotor BCI paradigms encode and decode brain signals to allow users to directly control output devices. In the interaction stage, co-adaptation has been used not only to facilitate system calibration but also to improve the communication rate. The adaptive classifiers significantly improve the accuracy and robustness of decoding. In addition, the modulation and demodulation techniques in telecommunication significantly facilitate the interaction of brain and computer in visual and auditory BCIs [77,78]. In the intelligence stage, AI techniques have been integrated to implement neural coding and decoding in BCIs. As a result, speech BCIs that decode and convert speech related neural activities to natural language have made unprecedented progress [79–81]. With a neural network-based encoder–decoder framework, the BCI system achieved high decoding accuracy at natural-speech rates with ECoG signals [82,83].

Sensorimotor BCIs have been successfully applied to the field of neuro-rehabilitation, especially for stroke rehabilitation. In the interface stage, the key technology involves generating robust brain signals to effectively control the rehabilitation devices. In the interaction stage, more attention has been paid to the active training modality that directly exercises the brain. Co-adaptive learning of the brain and algorithms enhances the performance of the sensorimotor BCI system, leading to a larger control dimension, higher accuracy, and greater speed [84]. In addition, neuromodulation methods such as TMS and TES have been applied to modulate cortical excitability and plasticity to promote recovery [29]. In the intelligence stage, the combination of intelligent rehabilitation systems with BCIs can further improve the efficiency of BCI-based rehabilitation. For example, the integration of BCIs and intelligent exoskeletons shows great potential in restoring motor functions of patients [85].

Challenges and opportunities

By looking at the development of the BCI technology through the stages of I3, we can draw three conclusions. First, efficient and effective brain computer communication lies at the core of research and development of BCI technology. Second, augmentation of human performance and well-being is the main goal of BCI research. Third, the progress of modern science and technology is the power source to boost the development and application of BCIs. We discuss each of these in the following sections.

Channel capacity

Channel capacity is defined as the maximum information rate that a communication channel can reliably transmit. BCI channel capacity can be measured by the information transfer rate (ITR), the amount of information transferred per unit time, in bits per second (bps). For existing BCI systems, insufficient channel capacity has become a major obstacle to the application of the BCI technology [86]. How to improve ITR has become a hot issue in BCI research.

Like communication systems in the physical world, a BCI communication system also consists of encoding and decoding components (Figure 3). The only difference is that the encoding process of signals is completed in the brain, which means that the encoding process is constrained by the physiological mechanism of the brain.

In common BCI systems, users encode discrete commands, generally called targets (e.g., the choices of characters in a BCI speller), into characteristic EEG signals. For such systems, a well-known calculation method of ITR based on Shannon information theory has been proposed [87]. Although some unreasonable assumptions added in the derivation process may lead to deviations from the estimate [88], this calculation method clearly identifies the main factors affecting ITR and the main ways to improve ITR at the macro level, and therefore has been widely used in the BCI field [89].

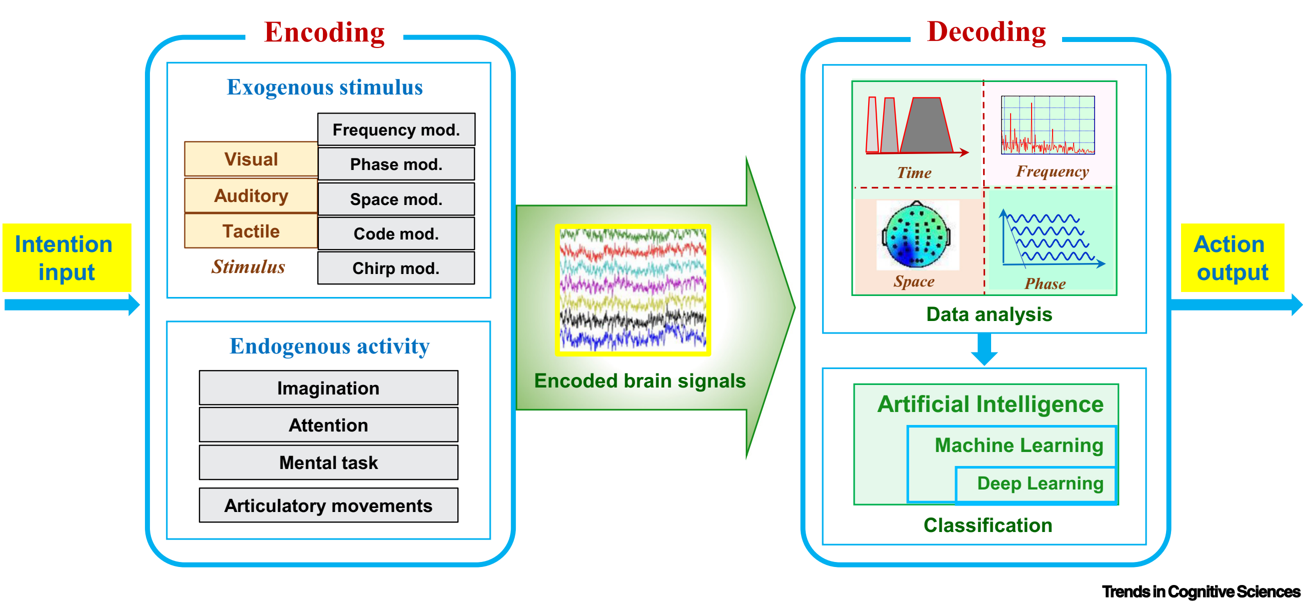

Figure 3. BCI as a communication system. In a BCI system, the user's intention can be converted into commands to control the external devices after the process of encoding, transmitting, and decoding. Brain signals can be encoded by exogenous stimuli or endogenous activities. After encoding, the information the user wants to express is transformed into specific brain activities through cognitive activities such as perception, attention, and imagination. The encoded brain signals can be transmitted to the decoder of the receiver locally or remotely. After analyzing and classifying the signals, the decoder can obtain the intention of the user for communication and control.

According to the definition of ITR [87], for BCI systems with discrete targets, the main ways to improve ITR include increasing the number of targets, improving the detection accuracy, and shortening the detection time. These three factors always influence each other. Firstly, as the number of targets increases, so too does the amount of information that must be transmitted each time. However, it is more difficult to identify each target correctly with more targets. The small number of targets (e.g., 2–40) in the existing BCI systems directly limits ITR. The study of VEP decoding in [90] indicates that there is still a lot of room to improve ITR by increasing the number of targets. Secondly, the detection accuracy can be improved by enhancing the quality of encoded brain signals [i.e., the signal-to-noise ratio (SNR)]. The neural activities recorded with implanted electrodes (i.e., spikes, LFP, and ECoG) generally show higher SNRs than the noninvasive approaches such as EEG. Meanwhile, other physiological information related to CNS activities may be integrated to improve the decoding of neural signals. For example, the variation of cardiac interbeat interval (IBI) induced by brain–heart interaction [91] and the blood oxygenation level dependent (BOLD) signals in fMRI [92,93] can be used to construct hybrid BCIs [62]. In addition, signal processing and machine learning algorithms can improve the accuracy and robustness in decoding. Finally, detection times might be shortened by considering both the encoding and decoding processes used. In the encoding process, there will be an inevitable delay from the beginning of target selection to the generation of corresponding brain signals (e.g., visual latency in visual BCIs). Therefore, choosing a paradigm with fast brain responses can be helpful. It is also important to shorten the data length required in target detection, which is closely related to the encoding efficiency and decoding performance.

In recent years, great progress has been made in improving ITR. In the research of BCI communication, the ITR has been upgraded from <1 bits/s [1] to ~5 bits/s [94]. In the research of brain signal decoding, the highest decoding rate of individual brain signals can reach ~20 bits/s [90]. However, there are still great challenges to further improve ITR in the future. One potential solution is to abandon the discrete targets-based encoding method and directly decode the brain signals produced in sensory perception and cognitive activities. For example, neural decoders can explicitly leverage kinematic and sound representations encoded in human cortical activities to synthesize audible speech [82,95]. This method not only greatly improves the channel capacity in BCI, but also makes the BCI-based communication and control more intuitive and natural.

BCI and human augmentation

Human augmentation usually refers to enhancing sense, action, and cognitive capabilities of a human (Figure 4) [96]. This enhancement may include either restoration or expansion [i.e., the ability to recover or compensate for lost functions (e.g., the loss of motor function caused by trauma) or the ability to enhance existing functions (e.g., enhancing the weight-bearing capacity of people through exoskeletons)].

The study of BCIs has always regarded human augmentation as an important direction and has made significant progress in the field of neural rehabilitation [97]. Currently, neurological and mental disorders cause many patients to lose their motor and language functions and may greatly affect their other cognitive abilities. Because the effects of medicine and surgery are often not satisfactory, BCIs provide a new solution to address the problem. The applications of brain-controlled prostheses to restore limb motor function [85,98] and brain-controlled typing to restore language function [78] are all successful examples. Additionally, BCI-based active training in neurorehabilitation plays an important role in the recovery of motor function of stroke patients with paralysis [4,99].

It is particularly noteworthy that BCI plays an important role in cognitive augmentation. Cognitive augmentation includes the improvement of attention, memory, judgment, reasoning, decision-

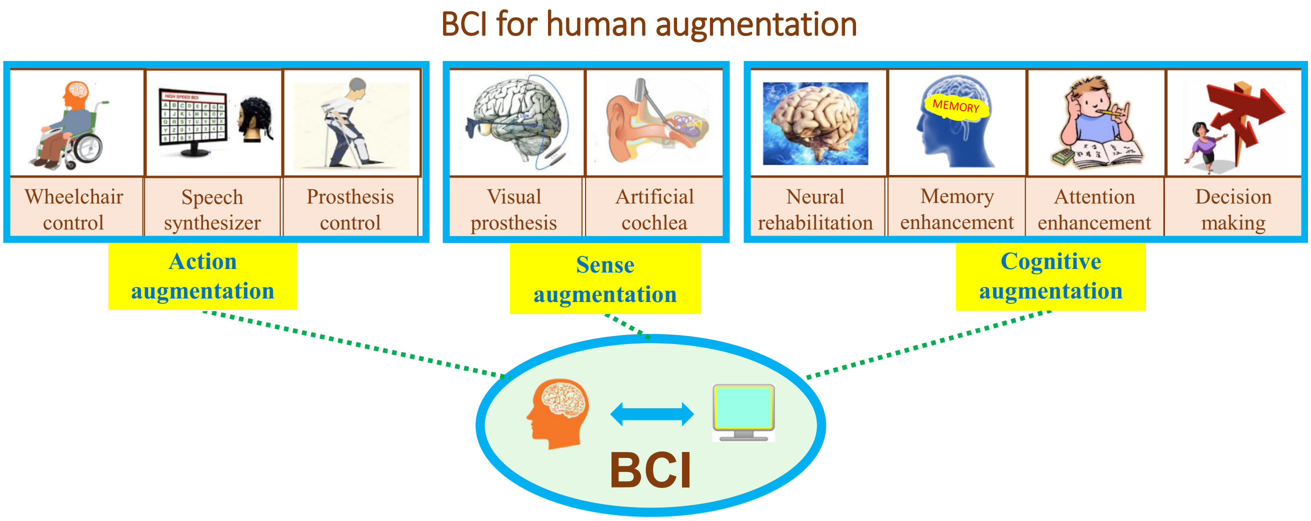

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Figure 4. BCI for human augmentation. BCI-based human augmentation has been used for enhancing the sense, action, and cognitive abilities of a human. In the applications of action augmentation, successful examples include brain controlled prosthesis for restoring limb movement function, brain controlled typing for restoring language function, and brain controlled wheelchair for helping patients move. In the applications of sense augmentation, visual and auditory functions can be effectively restored by directly stimulating the nervous system. In the applications of cognitive augmentation, BCIs can be used not only to improve the motor and cognitive abilities of stroke patients, but also to improve the abilities of memory, attention, and decision making for healthy people.

making, knowledge formation, and problem-solving abilities [100,101]. The basic technology in BCI-based cognitive augmentation involves neural information analysis and the corresponding intervention approaches such as neurofeedback training. BCI plays a unique role in cognitive enhancement because it supports direct communication and interaction between brain and machine. To treat cognitive decline due to disease or aging, BCI provides a variety of solutions to improve cognitive ability [4,75,102]. BCI also shows a wide range of potential applications to improve the cognitive abilities of healthy people [100]. For example, collaborative intelligence systems that integrate HI and AI provide a new solution to decision making problems, which not only makes the decision faster but also makes the decision more reasonable [10,103]. Furthermore, collaborative BCI systems that combine brain activities from multiple users have shown improved accuracy in various decision-making tasks [63,104,105].

At present, the implementation of BCI-based human augmentation still faces many difficulties. The first is to improve the function and performance of existing equipment, so that it can be easily used in daily life [106–108]. Secondly, it remains a significant challenge to establish a closed-loop system for real-time interaction between the CNS and the external devices [26].

BCI and AI

The two fields of BCI and AI originally developed relatively independently. However, with recent advances in both fields, a new situation of mutual promotion seems to have emerged [109]. With the rapid development of AI and machine learning technology, AI has been successfully applied to BCI systems (Figure 5A). On the one hand, AI is widely used to interpret massive multimodal neural signals in BCI systems [110,111]. On the other hand, AI-based intelligent devices can also encode and provide feedback of the collected environmental information to users, which improves the stability of operation in BCI systems [109].

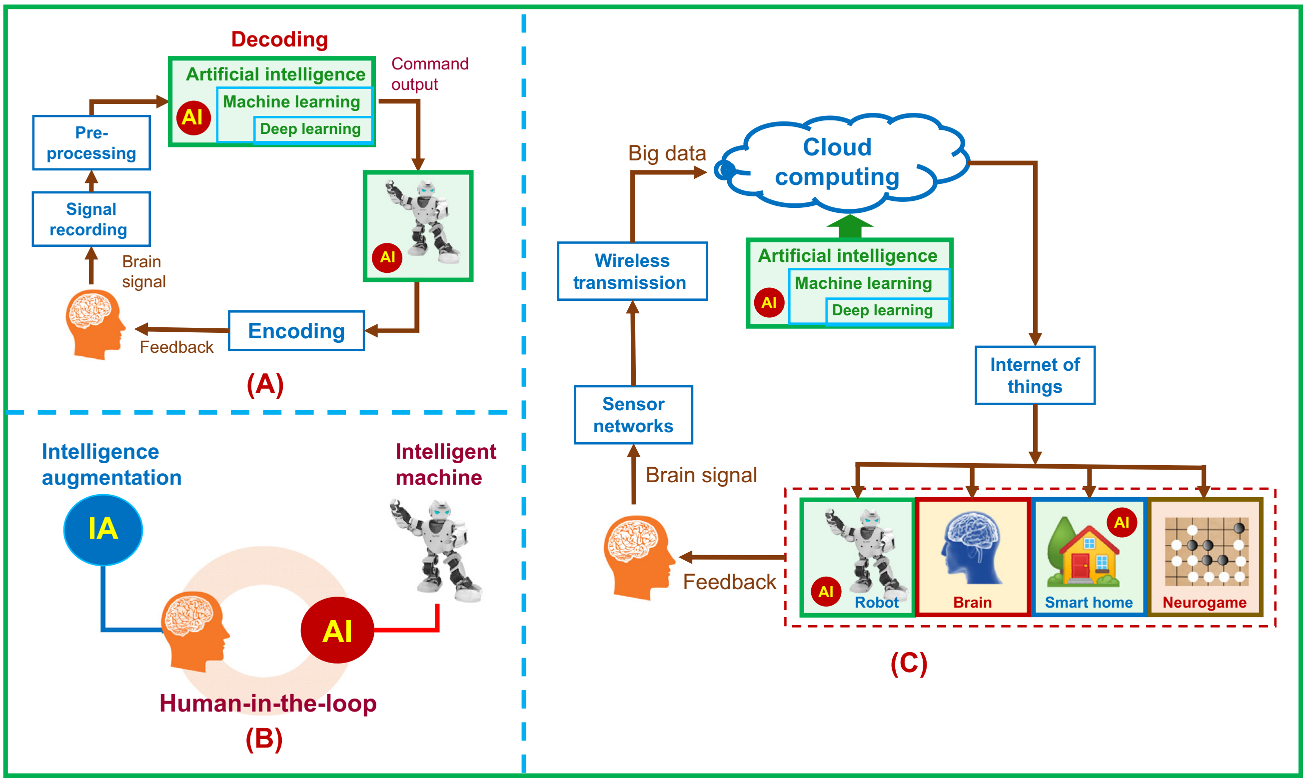

Figure 5. BCI and AI. (A) BCI with artificial intelligence (AI). Brain signal decoding is one of the core technologies of BCI. As artificial intelligence and machine learning, including deep learning, have obvious advantages in the interpretation of massive multimodal neural data, they have been successfully applied to the interpretation of brain signals in BCI. In addition, the intelligence of controlled objects (such as intelligent robots) can also effectively improve the performance of BCI. (B) AI and intelligence augmentation (IA). With BCI-based human-in-the-loop system, human beings will be able to use the AI technology to realize IA. (C) BCI with smart world. With the development of science and technology, the environment around us is becoming more and more intelligent, which also drives the prosperity of BCI. Sensor network realizes acquisition of multimodal information from the human body. Wireless transmission realizes high-speed transmission of big data. Cloud computing platform provides powerful computing resources for brain signal decoding. Internet of things (IoT) provides extensive interconnection between brain and objects, which can control remote robots and smart home, realize brain-to-brain communication, and provide a lot of business opportunities for neurogaming.

Although AI outperforms humans in some task-specific applications, it encounters difficulties in performing some complex tasks involving decision making, planning, and creativity. Because humans can quickly learn and apply conceptual information, the possibility of BCI-based hybrid intelligent system provides new opportunities to solve the problems encountered in the practical applications of AI [10,112]. By taking advantage of the synergy and complementarity of AI and HI, the hybrid system has achieved better results than any single working mode [45,113,114]. The combination of BCI and AI creates a human-in-the-loop system, in which human and AI work together to mutually improve performance [114]. With the help of the interaction and cooperation between the brain and the machine, it is possible to further realize human intelligence augmentation (IA) [115,116], which is also an important direction for the future development of BCI (Figure 5B).

With the development of science and technology, especially the development of AI, internet of things (IoT), big data, cloud computing, virtual reality (VR), augmented reality (AR), and other information technologies, the environment around us has become more and more intelligent [114,117,118]. The new technologies will inevitably impact our work and lives. In fact, people have begun to use BCIs to communicate with and control the physical world and VR, including connecting the IoT to control objects in an infinite space [119,120]. Remote brain-to-brain communication has even been realized [38,121]. As shown in Figure 5C, the extensive connection and control function not only enables the disabled to improve their quality of life, but also enables healthy people to enhance and expand their abilities [100,122,123]. It is believed that, based on the platform of BCI technology, the model that integrates HI, AI, and smart world technologies, will influence society and greatly benefit humans [114,124].

Concluding remarks

With the development and integration of cognitive neuroscience, information science, and engineering technology, BCIs have entered a new stage of rapid development [125–127]. This paper briefly reviews the development of BCIs and summarizes the existing BCI technology by an evolutionary model of I3. The model shows that with the advancement of technology and the deepening of research, the connection between the brain and the computer has become increasingly close, and the information exchange between them has developed from sensation and perception to cognition, leading to seamless connection and cognitive collaboration [128]. The deep integration of HI and AI shows the new trend in the future development of BCIs.

As an interdisciplinary research field, BCI's future development depends on the progress of neuroscience and engineering technology. From the perspective of neuroscience, more fully understanding the function and working mechanism of the brain is the basis for future success of BCIs [129]. From the engineering perspective, the applications of multimodal and large-scale neuronal recording, ultra-high-speed broadband wireless signal transmission (5G and beyond), and super data processing capability of cloud platform are the directions of future development [108].

Overall, BCI technology is still in its infancy, although great progress has been made in recent years. Most of the existing BCI systems have only been demonstrated in the laboratories and are still far away from practical usages. The reliability and accessibility must be improved so that BCIs can become an indispensable tool in daily life of the disabled and healthy people (see Outstanding questions).

Outstanding questions

How can we develop brain imaging/monitoring systems with both high temporal and spatial resolutions?

Can we develop high-performance BCI systems under the very limited knowledge of brain science? Also, can we develop brain inspired artificial intelligence systems as smart as humans?

How can we develop noninvasive or non-surgical methods for transducer implant? How can we solve the problem of biocompatibility of implanted transducers in brain tissues?

What is the maximum of ITR for invasive or noninvasive BCI systems? Is it possible to display your mind directly on the monitor in front of you?

Does BCI illiteracy really exist? Is the occurrence of users with poor performance because the BCI system itself is not perfect, or is the mechanism of nervous system different across individuals?

What is the neural mechanism of cognitive augmentation? Can neurofeedback or BCI training be applied to a wide range of people? Can the training effect continue to augment human function?

How should we deal with ethical issues related to BCI? Should the invasive methods be used in healthy people? Can mind reading technology gain access to private information?

Acknowledgments

This study is supported in part by the Key Research and Development Program of Guangdong Province (No. 2018B030339001), the National Key Research and Development Program of China (No. 2017YFB1002505), the Strategic Priority Research Program of Chinese Academy of Science (No. XDB32040200), and the National Natural Science Foundation of China (No. 61671424).

Declaration of interests

No interests are declared.

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